

solution

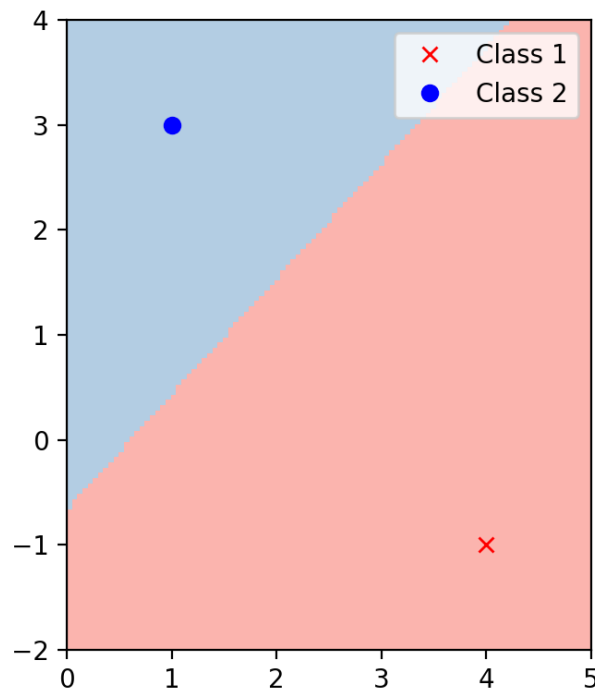
Question 1

(a)

We can derive the decision rule following the Bayes rule ($\underline{X} = [x_1, x_2]^T$):

$$\begin{aligned} P(S_i|X=x) &\propto P(X=x|S_i)P(S_i), i=1,2 \\ \ln \frac{P(S_1|X=x)}{P(S_2|X=x)} &= \ln \frac{P(X=x|S_1)P(S_1)}{P(X=x|S_2)P(S_2)} \\ &= \ln \frac{N(\underline{x}, \underline{m}_1, \underline{\Sigma}_1)}{N(\underline{x}, \underline{m}_2, \underline{\Sigma}_2)} \\ &= \ln \frac{|\underline{\Sigma}_1|^{-1/2} \exp\left(-\frac{1}{2}(\underline{x} - \underline{m}_1)^T \underline{\Sigma}_1^{-1}(\underline{x} - \underline{m}_1)\right)}{|\underline{\Sigma}_2|^{-1/2} \exp\left(-\frac{1}{2}(\underline{x} - \underline{m}_2)^T \underline{\Sigma}_2^{-1}(\underline{x} - \underline{m}_2)\right)} \\ &= -\frac{1}{2}\left[(\underline{x} - \begin{bmatrix} 1 \\ -1 \end{bmatrix})^T \begin{bmatrix} 2 & 3 \\ 3 & 6.5 \end{bmatrix}^{-1} (\underline{x} - \begin{bmatrix} 1 \\ -1 \end{bmatrix}) - (\underline{x} - \begin{bmatrix} 2 \\ 3 \end{bmatrix})^T \begin{bmatrix} 2 & 3 \\ 3 & 6.5 \end{bmatrix}^{-1} (\underline{x} - \begin{bmatrix} 2 \\ 3 \end{bmatrix})\right] \\ &= 1.375x_1 - 1.25x_2 - 0.8125 \end{aligned}$$

So we have decision rule that if $\ln \frac{P(S_1|X=x)}{P(S_2|X=x)} > 0$, then x belongs to class 1, else x belongs to class 2.

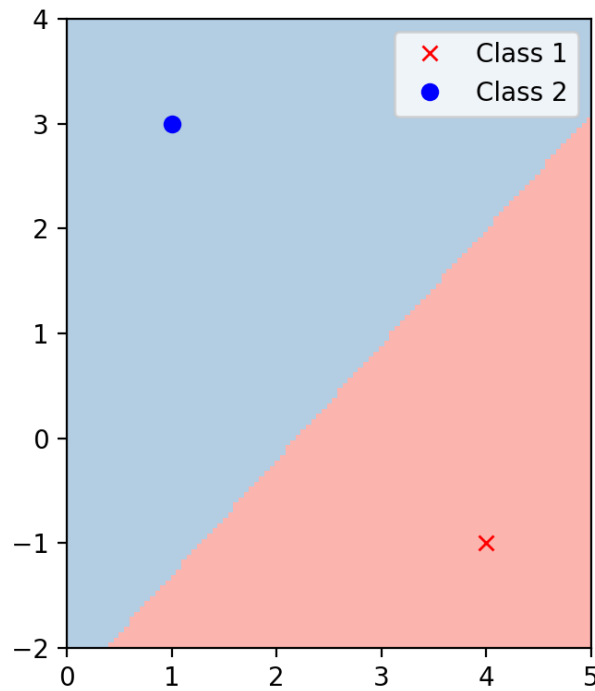


(b)

We can derive the decision rule following the Bayes rule:

$$\begin{aligned}
P(S_i|X=x) &\propto P(X=x|S_i)P(S_i), i=1,2 \\
\ln \frac{P(S_1|X=x)}{P(S_2|X=x)} &= \ln \frac{P(X=x|S_1)P(S_1)}{P(X=x|S_2)P(S_2)} \\
&= \ln \frac{N(\underline{x}, \underline{m}_1, \underline{\Sigma}_1)P(S_1)}{N(\underline{x}, \underline{m}_2, \underline{\Sigma}_2)P(S_2)} \\
&= \ln \frac{P(S_1)|\underline{\Sigma}_1|^{-1/2} \exp\left(-\frac{1}{2}(\underline{x} - \underline{m}_1)^T \underline{\Sigma}_1^{-1}(\underline{x} - \underline{m}_1)\right)}{P(S_2)|\underline{\Sigma}_2|^{-1/2} \exp\left(-\frac{1}{2}(\underline{x} - \underline{m}_2)^T \underline{\Sigma}_2^{-1}(\underline{x} - \underline{m}_2)\right)} \\
&= \ln \frac{1}{9} + \left(-\frac{1}{2}\left(\underline{x} - \begin{bmatrix} 1 \\ -1 \end{bmatrix}\right)^T \begin{bmatrix} 2 & 3 \\ 3 & 6.5 \end{bmatrix}^{-1} (\underline{x} - \begin{bmatrix} 1 \\ -1 \end{bmatrix}) - (\underline{x} - \begin{bmatrix} 2 \\ 3 \end{bmatrix})^T \begin{bmatrix} 2 & 3 \\ 3 & 6.5 \end{bmatrix}^{-1} (\underline{x} - \begin{bmatrix} 2 \\ 3 \end{bmatrix})\right) \\
&= 1.375x_1 - 1.25x_2 - 3.00972
\end{aligned}$$

So we have decision rule that if $\ln \frac{P(S_1|X=x)}{P(S_2|X=x)} > 0$, then x belongs to class 1, else x belongs to class 2.



Question 2

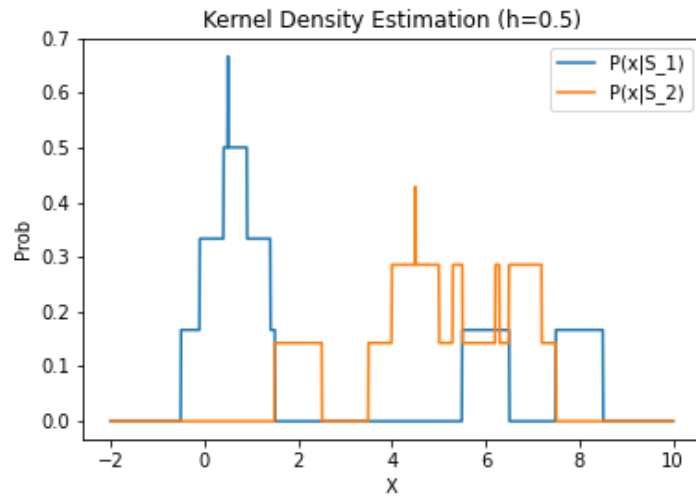
(a)

$h=0.5$,

$$\phi(x) = \begin{cases} 1, & -0.5 \leq x \leq 0.5 \\ 0, & \text{otherwise} \end{cases}$$

$$P(x|S_1) = \frac{1}{6} \sum_{i=1}^6 \phi(x - x_i)$$

$$P(x|S_2) = \frac{1}{7} \sum_{i=1}^7 \phi(x - x_i)$$



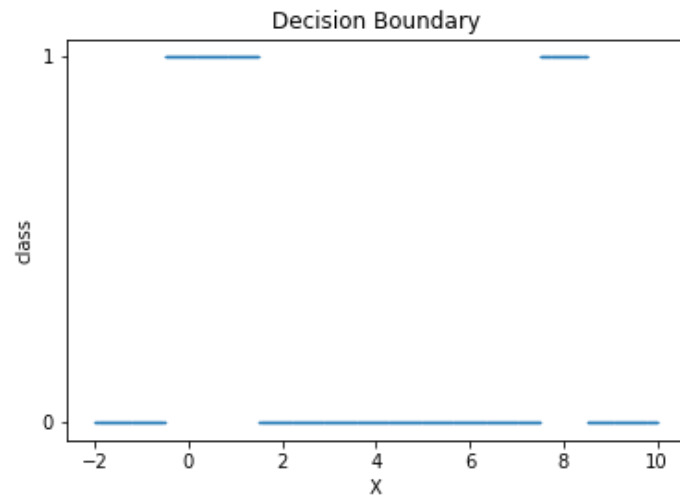
(b)

The prior is $P(S_1) = \frac{6}{13}, p(S_2) = \frac{7}{13}$

(c)

Following Bayes rule, we can derive the decision rule as follows:

$$\begin{aligned} \frac{P(S_1|X=x)}{P(S_2|X=x)} &= \frac{P(X=x|S_1)P(S_1)}{P(X=x|S_2)P(S_2)} \\ &= \frac{\sum_{i=1}^{n_1} \phi(x-x_i)}{\sum_{i=1}^{n_2} \phi(x-x_i)} \end{aligned}$$



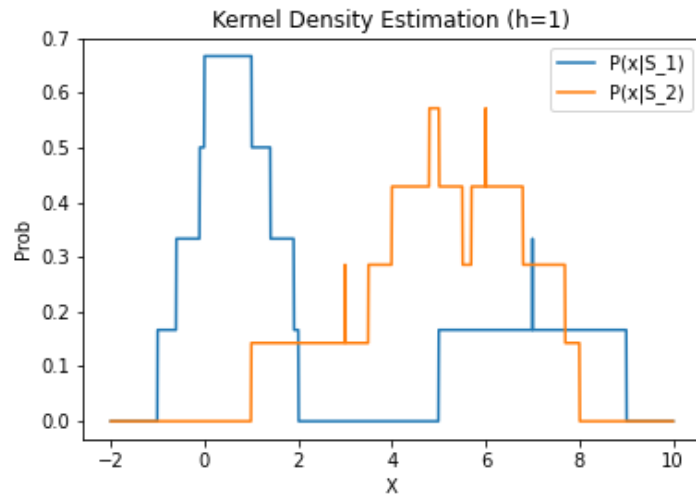
(d)

$h=1,$

$$\phi(x) = \begin{cases} 1, & -1 \leq x \leq 1 \\ 0, & \text{otherwise} \end{cases}$$

$$P(x|S_1) = \frac{1}{6} \sum_{i=1}^6 \phi(x-x_i)$$

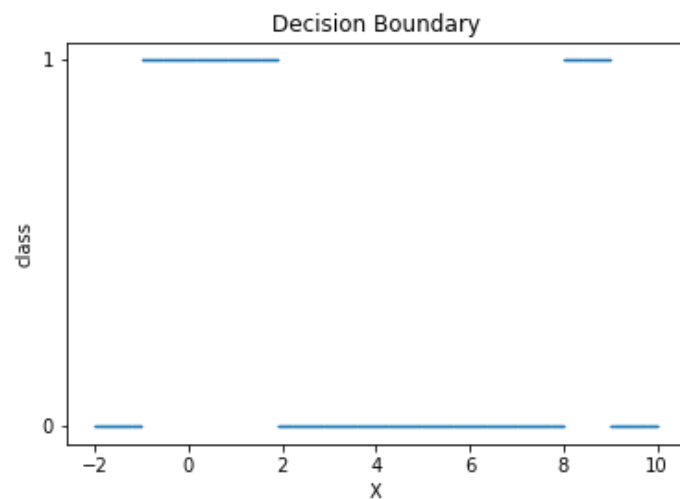
$$P(x|S_2) = \frac{1}{7} \sum_{i=1}^7 \phi(x-x_i)$$



The prior is $P(S_1) = \frac{6}{13}, p(S_2) = \frac{7}{13}$

Following Bayes rule, we can derive the decision rule as follows:

$$\begin{aligned} \frac{P(S_1|X=x)}{P(S_2|X=x)} &= \frac{P(X=x|S_1)P(S_1)}{P(X=x|S_2)P(S_2)} \\ &= \frac{\sum_{i=1}^{n_1} \phi(x-x_i)}{\sum_{i=1}^{n_2} \phi(x-x_i)} \end{aligned}$$



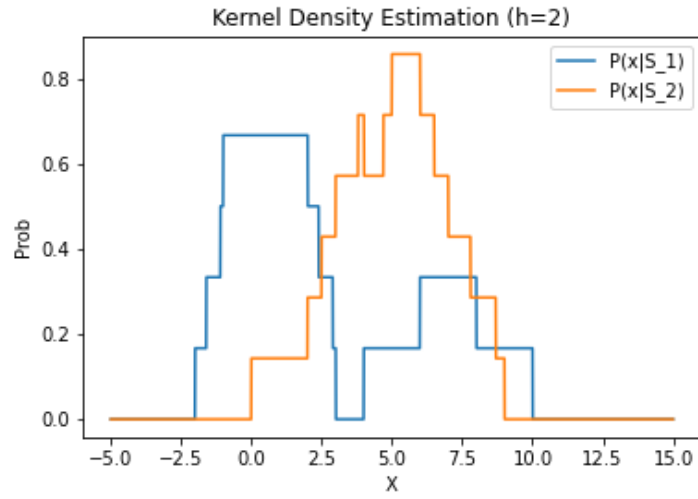
(e)

h=2,

$$\phi(x) = \begin{cases} 1, & -2 \leq x \leq 2 \\ 0, & \text{otherwise} \end{cases}$$

$$P(x|S_1) = \frac{1}{6} \sum_{i=1}^6 \phi(x-x_i)$$

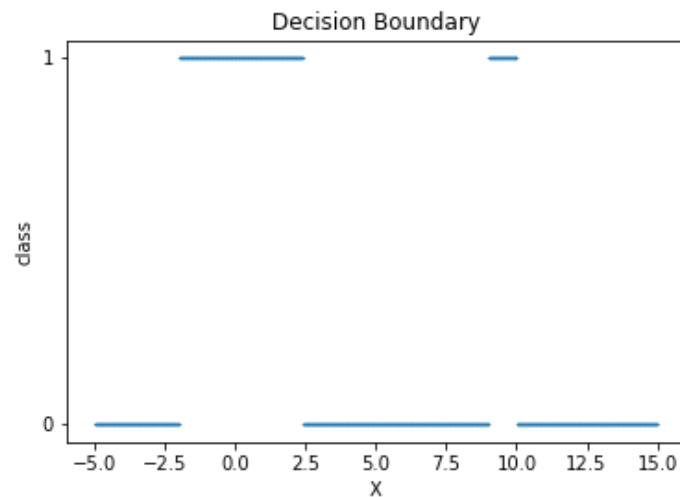
$$P(x|S_2) = \frac{1}{7} \sum_{i=1}^7 \phi(x-x_i)$$



The prior is $P(S_1) = \frac{6}{13}, p(S_2) = \frac{7}{13}$

Following Bayes rule, we can derive the decision rule as follows:

$$\begin{aligned} \frac{P(S_1|X=x)}{P(S_2|X=x)} &= \frac{P(X=x|S_1)P(S_1)}{P(X=x|S_2)P(S_2)} \\ &= \frac{\sum_{i=1}^{n_1} \phi(x-x_i)}{\sum_{i=1}^{n_2} \phi(x-x_i)} \end{aligned}$$



Question 3

(a)

For $x = 0$, we can compute the distance of each point to it as follows:

$$d_1 = 0.9, d_2 = 0.7, d_3 = 0.5, d_4 = 0.3, d_5 = 0.1, d_6 = 0.1, d_7 = 0.3, d_8 = 0.5, d_9 = 0.7, d_{10} = 0.9$$

The nearest 4 points are $(-0.1, 0.01), (0.1, 0.01), (-0.3, 0.09), (0.3, 0.09)$

$$\text{Thus, the estimated } \hat{y}(x) = \frac{0.01+0.01+0.09+0.09}{4} = 0.05$$

For $x = 0.4$, we can compute the distance of each point to it as follows:

$$d_1 = 1.3, d_2 = 1.1, d_3 = 0.9, d_4 = 0.7, d_5 = 0.5, d_6 = 0.3, d_7 = 0.1, d_8 = 0.1, d_9 = 0.3, d_{10} = 0.5$$

The nearest 4 points are $(0.3, 0.09), (0.5, 0.25), (0.1, 0.01), (0.7, 0.49)$

$$\text{Thus, the estimated } \hat{y}(x) = \frac{0.09+0.25+0.01+0.49}{4} = 0.21$$

(b)

$$y(0) = 0, y(0.4) = 0.16$$

Therefore, the mean square error is $MSE = \frac{1}{2}((0.05 - 0)^2 + (0.21 - 0.16)^2) = 0.0025$

(c)

$$k(\underline{x}, \underline{x}_n) = 1 - \frac{d(\underline{x}, \underline{x}_n)}{d_{\max}}$$

For $x = 0$, we can apply the kernel regression as follows:

$$d_1 = 0.9, d_2 = 0.7, d_3 = 0.5, d_4 = 0.3, d_5 = 0.1, d_6 = 0.1, d_7 = 0.3, d_8 = 0.5, d_9 = 0.7, d_{10} = 0.9$$

$$d_{\max} = 0.5$$

$$k_1 = -0.8, k_2 = -0.4, k_3 = 0, k_4 = 0.4, k_5 = 0.8, k_6 = 0.8, k_7 = 0.4, k_8 = 0, k_9 = -0.4, k_{10} = -0.8$$

$$\hat{y}(x) = \frac{\sum_{i \in N_4} k_i y_i}{\sum_{i \in N_4} k_i} = 0.0367$$

where N_4 denotes the nearest neighbor set of size 4.

For $x = 0.4$, we can apply the kernel regression as follows:

$$d_1 = 1.3, d_2 = 1.1, d_3 = 0.9, d_4 = 0.7, d_5 = 0.5, d_6 = 0.3, d_7 = 0.1, d_8 = 0.1, d_9 = 0.3, d_{10} = 0.5$$

$$d_{\max} = 0.5$$

$$k_1 = -1.6, k_2 = -1.2, k_3 = -0.8, k_4 = -0.4, k_5 = 0, k_6 = 0.4, k_7 = 0.8, k_8 = 0.8, k_9 = 0.4, k_{10} = 0$$

$$\hat{y}(x) = \frac{\sum_{i \in N_4} k_i y_i}{\sum_{i \in N_4} k_i} = 0.1967$$

where N_4 denotes the nearest neighbor set of size 4.

$$y(0) = 0, y(0.4) = 0.16$$

Therefore, the mean square error is $MSE = \frac{1}{2}((0.0367 - 0)^2 + (0.1967 - 0.16)^2) = 0.00134$